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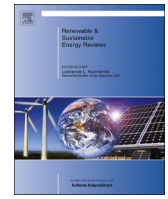

Carbon dioxide emissions intensity of Portuguese industry and energy sectors: A convergence analysis and econometric approach

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A R T I C L E I N F O

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A B S T R A C T

Given the relevance of energy and pollution issues for industrialised countries and the importance of industry and energy sectors to the achievement of their economic and environmental goals, it is important to know if there is a common pattern of emissions intensity, fuel intensity and energy intensity, between industries, to know if it justifies a more specific application of energy policies between sectors, which sectors have the greatest potential for reducing energy use and which are the long term effects of those specific variables on the mitigation of emissions. We found that although there is literature on decomposition of effects that affect emissions, the study of the convergence and of the relationships between these variables does not include ratios or effects that result from the decomposition analysis. Thus, the above questions are not answered, much less for the Portuguese reality. The purpose of this paper is to study: (i) the existence of convergence of some relevant ratios as Carbon Dioxide (CO_2) emissions intensity, CO_2 emissions by fossil fuel consumption, fossil fuel intensity, energy intensity and economic structure, between industry and energy sectors in Portugal, and (ii) the influence that the consumption of fossil fuels, the consumption of aggregate energy and GDP have on CO_2 emissions, and the influence that the ratios in which CO_2 emissions intensity decomposes can affect that variable, using an econometric approach, namely Panel corrected standard errors estimator. We concluded that there is sigma convergence for all ratios with exception of fossil fuel intensity. Gamma convergence verifies for all ratios, with exception of CO_2 emissions by fossil fuel. From the econometric approach we concluded that the considered variables have a significant importance in explaining CO_2 emissions and CO_2 emissions intensity.

Contents

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1. Introduction

The energy-related Carbon Dioxide (CO_2) emissions, in the European Union (EU)-15, produced by the industry sector, changed between 1990 and 2010 from 37% to 30%. The direct effect (fuel driven) and the indirect effect (due to industrial electricity consumption) both contribute to lowering these emissions. At worldwide level, the industry sector accounted for 26% of global energy use and 18.5% of global CO_2 emissions in 2010 [1].

Portugal managed to meet Kyoto Target for the period 2008–2012. In 2011 it showed a level of emissions 16% higher than the 1990 level (its limit was 27%) [2]. However, the goals of reducing emissions are not restricted to this period. In 2009 a new package of environmental measures was adopted at the EU level, known as the 20–20–20 targets: by 2020 there should be a 20% reduction of Greenhouse Gases (GHG) emissions compared with 1990, 20% share of renewable energy in EU energy consumption, and energy improvement by 20%.

The main gas emitted in Portugal is CO_2, representing approximately 74% of total GHGs emissions expressed as global warming potential (GWP) weighted emissions [2]. The industry and energy sectors are the major emitters of CO_2 (68.2%), despite its weight declined in favour of the services and transport sectors (Fig. A1 in Appendix A).

Indeed, the emissions intensity and the energy intensity of the industry and energy sectors are well above the average of the economy (Figs. A2 and A3 in Appendix A), which highlights the importance of looking to these sectors as paramount in achieving environmental goals.

The question becomes even more relevant if we observe that most of the energy used comes from fossil fuels (coal, oil and natural gas), and that this percentage is much higher in the industry and energy sectors than the average for the Portuguese economy (Fig. A4 in Appendix A). This explains the relative high value of intensity of emissions in these sectors. In 2009, this percentage was of 95.3% for the industry and energy sectors compared with 82.4% of the average of the economy. However, this path is changing with a progressive enhancement of renewable energy, in particular, the expansion of windmills [1].

Robaina-Alves and Moutinho [3] refer that in Portugal there are 5 industry and energy sectors that can be distinguished from the others by their emissions intensity: mining and quarrying, the manufacturing of coke and refined petroleum products, the manufacturing of chemicals and chemical products, the manufacturing of rubber and plastic products, and other non-metallic mineral products and electricity, gas, steam and air-conditioning supply.

Although, the European Carbon Market imposes different caps to the various sectors,[1] they are exposed to a common commitment, and to the uniformity of public policies, for example, the policy of reducing fossil fuel intensity and promoting renewable energy sources supporting the mitigation of CO_2 emissions intensity.

Therefore, it is important to (i) know if there is a common pattern of emissions intensity, fuel intensity and energy intensity, between industries (convergence), to know if it justifies a more specific application of energy policies between sectors, and which sectors have the greatest potential for reducing energy use; and (ii) study the long term effects of those specific variables on the mitigation of CO_2 emissions. These two approaches could give relevant information for the policy making with regard to the timing of policy interventions and to the choice of policy instruments. We found that although there is literature on decomposition of effects that affect emissions, the study of the convergence and the relationships between these variables does not include ratios or effects that result from the decomposition analysis. Thus, the above questions are not answered, much less for the Portuguese reality.

As a consequence, the purpose of this paper is to study (i) the existence of convergence of some relevant ratios as CO_2 emissions intensity, CO_2 emissions by fossil fuel consumption, fossil fuel intensity, energy intensity and economic structure, between industry and energy sectors in Portugal, and (ii) the influence that the consumption of fossil fuels, the consumption of aggregate energy and GDP have on CO_2 emissions, and the influence that the ratios in which CO_2 emissions intensity decomposes can affect that variable, using an econometric approach.

In two different and complementary methodologies, as the convergence analysis, together with the use of the Panel Corrected Standard Errors (PCSE) estimator, we conducted the analysis for 16 industry and energy sectors (Group A) and for the sub-group of the 5 most polluting sectors (concerning emissions intensity), composed mainly by energy sectors (Group B). This methodology allows one, on the one hand, to observe whether there is a common behaviour among the variables determining the emissions for the two groups of industries. If so, then it is useful to study the influence in terms of elasticity of these same variables on emissions.

We concluded that there is sigma convergence for all ratios with exception of fossil fuel intensity. The harmonisation is greater in group B for the intensity of emissions and for energy intensity. Gamma convergence verifies for all ratios, with exception of CO_2 emissions by fossil fuel and fossil fuel intensity in group B. From the econometric approach we concluded that the considered variables have a significant importance in explaining CO_2 emissions and CO_2 emissions intensity. In the last case, elasticities of CO_2 emissions by fossil fuel consumption, fossil fuel consumption by energy consumption, energy intensity and the economic structure, are respectively of 113%, 97%, 96% and 98% on the dependent variable, ceteris paribus. For group B the magnitude of the impacts is greater.

The remainder of this paper is organised as follows. Section 2 presents the literature review. Section 3 describes the data and methodology. The main results are reported in Section 4 and Section 5 concludes.

2. Literature review

There are many studies that decompose CO_2 emissions intensity of industry into several factors or effects. See for instance Huang [5], Sinton and Levine [6], Hamilton and Turton [7], Paul and Bhattacharya [8], Liao et al. [9], Ma and Stern [10], Zhang et al. [11], Zhao et al. [12], Oh et al. [13], Akbostanci et al. [14], Sheinbaum-Pardo et al. [15], O'Mahony et al. [16] and Miketa [17] for studies of energy intensity or CO_2 emissions intensity decomposition in industrial sectors. The following studies are known for Portugal: Diakoulaki and Mandaraka [18], Hatzigeourgiou et al. [19] and Robaina-Alves and

[1] See Robaina-Alves et al. [4], for a sectoral analysis of the effects of this market in Portugal.

Moutinho [3], where the 'complete decomposition' technique to examine CO_2 emissions intensity and its components is used. These studies are useful for understanding the methods of decomposition of energy-related CO_2 emissions and for identifying the factors that have influenced the changes in the level of energy-related CO_2 emissions. The most common are the output effect, the energy mix effect, the energy intensity effect and the structural effect. Hatzigeougiou et al. [19] also use the population effect and Diakoulaki and Mandaraka [18] the utility mix effect.

To see if there is a common pattern in the pollution path or in the energy consumption path of different countries or sectors, there are works that analyse energy intensity or emissions intensity convergence. For instance, Robinson [20] uses the concepts of Beta convergence and stochastic convergence to study the ambition to create a single European Electricity Market. Newman et al. [21], assess Beta convergence of natural gas prices in European markets. Blot and Serranito [22], use the concepts of Sigma-convergence, to justify the unit-root test analysis for the sectorial breaks in the fiscal policies in European Monetary Union (EMU).

Especially in sectorial industrial studies, among others, Strazicich and List [23], examined the period 1960–1997 of carbon dioxide emissions in twenty-one industrial countries and tested the convergence for stochastic and conditional convergence. Using both panel unit root tests and cross-section regressions, they found significant evidence that CO_2 emissions converged. Also Panopoulou and Pantelidis [24] using Phillips and Sul [25] methodology, concluded that there is convergence for 128 countries in the previous period to 1960–2003, and that in a more recent period they distinguished two distinct groups of countries that converge together. Camarero et al. [26] using the same methodology, test the convergence of CO_2 emissions intensity and their determinants among OECD countries over the period 1960–2008, and they find that differences in emissions intensity convergence are more determined by differences in convergence of the carbonisation index rather than differences in the energy intensity.

Similarly to Panopoulou and Pantelidis [24], Mulder and De Groot [27] concluded the existence of convergence for a more recent period, specifically after 1995, for OECD countries and 50 sectors. This is mainly due to changes in the sectoral composition if economies, as Manufacturing sectors loss importance, in favour of services, which present a strong degree of convergence.

Liddle [28], analysed the aggregate and sectoral convergence in the electricity intensity and energy intensity in IEA/OECD countries, and concluded that there is convergence, since the countries with the highest intensities exhibit downward trends, and many of the other countries show slight increasing trends. Aggregate electricity intensity has converged among countries, but less dramatically than aggregate energy intensity. The three analysed sectors (residential, industry and commercial) have converged at different rates. Commercial electricity intensity has a distribution that is most characterised by a bell-shape while industry and residential electricity intensity have more bimodal distributions.

Jakob et al. [29] studied how the process of economic development may affect the patterns of emissions and energy use at the sectoral level. For that analyzes the economic convergence and convergence of emissions. Concluded for 30 developing countries that economic convergence not imply convergence in emissions, while in 21 industrialised countries was found that it was possible a greater economic growth without increasing energy consumption or emissions.

For European Countries Jobert et al. [30] and Herrerias [31] analysed the existence of convergence in emissions, and found different conclusions. The first ones, concluded that countries converge, but that they are different in emission trends, convergence speeds and on the impact of the ratio (industry/GDP) on emissions. The second found a period of convergence from 1946 to 1975 but a period of divergence from 1976 to 2007.

We can point the study of Boeringer-Welsh [32] with a different methodology, based on a general equilibrium model for various regions and studying the possibility of convergence of per capita emissions, considering the existence of a global market for emissions. The study reveals that there is a need for stringent future emissions reduction at the global level and that changes in the terms of trade play a key determinant of the overall welfare effects. This methodology contrasts, but at the same time can be complemented with information coming from econometric models. The econometric models have advantages because they use information from long time series and are based on this long-term relationship to establish causal effects between variables. The econometric models are simpler drafting and interpretation, unlike the general equilibrium models, which require much more detailed and complex information, to establish the relationships between all the variables in a given year benchmark. But at a disadvantage, the econometric models do not consider all the flows of the economy simultaneously. As part of this study believe that the econometric methodology is appropriate because to apply energy and environmental policies becomes necessary to understand how certain variables behaved and influenced each other in the past, so as to understand what impact the policies that affect those variables will have in the future.

To study the influence of determinant variables on pollution we can refer to Hettige et al. [33], who used the panel OLS (fixed effects and random effects) for industrial water pollution, or Stern [34], who applied a panel data set for sulphur emissions using a econometric decomposition approach to estimate the Environmental Kuznets Curve (EKC) model. Cole et al. [35], used econometric panel estimation OLS with fixed effects and random effects to study the variables that influence pollution intensity.

Others studied the influence of some variables on energy intensity, like Miketa [17], which conducted the panel analysis for ten manufacturing industries of 39 countries over 1971–1996. The results of this study show that capital formation has the effect of increasing energy intensity and this effect is stronger where sectorial output is larger.

3. Data and methodology

Following the study of Robaina and Moutinho [3], whose main objective was to study the decomposition of explanatory CO_2 emissions in Portugal at the sectoral level, was identified a group of 16 industries (group A) and a subgroup of 5 industries (group B) with higher levels of emissions intensity in the total of 36 economic sectors studied.

The evolution of CO_2 emissions intensity between sectors can be exploited mainly with measures of convergence, with a focus on literature for 3 measures of convergence: sigma convergence, βeta convergence and Gamma convergence. These measures capture the potential explanation that the sectors with lower initial levels of emission intensity should genuinely experience a higher growth of pollution and thus eventually "catch-up" with the most polluting sectors. In practice, the "catch-up" occurs between similar sectors whose intensity of fossil energy and non-fossil consumed excels in different moments of time. Accordingly, the industrial sectors with structural differences in energy consumption and sources of fossil and non-fossil resources used in production tend to increase toward its own level of pollution, and thus the convergence becomes conditioned to the specific characteristics of the own industry.

Our study includes jointly sectional data (industry and energy sectors) and temporal data, and assuming that the intensities of the emissions in industrial sectors are not constant, it fits the

econometric technique of Panel-Corrected Standard Error (PCSE) in the sectoral context to jointly examine the following questions:

(i) Sectoral effect dimension that is present in different industries, so this influences the variance, violating in this way, the hypothesis of equality of variance in the cross-sectional component of the sample;
(ii) effect of cross-sectional dependence, since industrial policies are transverse and there are joint commitments for further mitigation of emissions in the country; and
(iii) effect of temporal evolution in terms of emissions intensity, energy intensity and energy mix, which justifies checking the possible existence of serial correlation of the series of these variables.

Given that, until better knowledge is the first time that a study jointly applies these two techniques to analyse the sectoral level, since in most of the studies referenced in the literature these techniques are applied individually to explain the relationship between emissions and economic growth but at the level of countries and regions.

All data was obtained from the INE (National Accounts). We present a table in Appendix A with the sectors included in group A and B. We considered the period 1996–2009, because it was the most recent period for which we had common data for all variables.

We considered data of CO_2 emissions from fossil origin, in 10^3 t. To obtain fossil fuels consumption, we added INE data of natural gas, coal and lignite, petroleum coke, fuel oil, diesel oil, motor gasoline, LPG and other petroleum products, in GJ. We used consumption of energy data (emissions relevant), in GJ, and Gross Domestic Product from the production side at market and constant prices, in 10^6 Euros.

3.1. Convergence analysis

The convergence analysis intends to see if stochastic differences in the long-term, between industrial sectors, means that accumulated random differences in the short-term constitute an explanation to see if the shocks on those series persist over time.

The convergence was calculated for five ratios, in the two groups of industries in Portugal. The ratios are (i) CO_2 emissions/GDP (emissions intensity), (ii) CO_2 emissions/fossil fuels consumption (denoted by CI), (iii) fossil fuels consumption/total energy consumption (denoted by CE), (iv) energy/GDP (denoted by energy intensity or EI) and (v) sector GDP/GDP (denoted by economic structure or ES).

Two measures of convergence were calculated (following Boyle and McCarthy [36]): sigma convergence and gamma convergence.[2] Sigma convergence tracks the inter-temporal change. For instance for the ratio CE it is calculated as

$$\sigma = \left(\frac{\mathrm{var}(CE_{ti})/\mathrm{mean}(CE_{ti})}{\mathrm{var}(CE_{t0})/\mathrm{mean}(CE_{t0})} \right)$$

where ti is the current year and $t0$ is the first year (1996). If we observe a fall in this measure it means that there is sigma convergence.

Gamma convergence is useful to analyse if the most polluting sectors occupy the same position at the beginning and at the end of the considered period, and if the importance of the emissions intensity drivers remains the same throughout this period. For instance for the ratio CE it is calculated as:

$$\gamma = \left(\frac{\mathrm{var}(RCE_{ti} + RCE_{t0})}{\mathrm{var}(RCE_{t0} \times 2)} \right)$$

Gamma ranges from zero to unity. If it is close to zero it means that there was mobility in the position of the sectors. RCE is the rank of the sector in current year ti or in the first year $t0$, for the ratio CE.

3.2. Econometric approach

Given the nature of our sample, it seems reasonable to assume that the observations for the different variables studied in the industries tend to be correlated, and present the problem of cross dependence. This problem is particularly difficult to treat empirically, since this might occur due to a variety of reasons as for instance unobserved shocks common in some series. Heterogeneous and deterministic parameters also pose additional difficulties and how they are treated under the null hypothesis and under the alternative hypothesis may affect the result of empirical analysis.

The most common methods, Ordinary Least Squares (OLS) or Generalised Least Squares (GLS), are usually used to estimate the coefficients in a given regression, reveal errors adjusted for correlation within a company or industry. So, on one hand the standard deviations of OLS estimators or GLS are biased and inefficient when the residuals are independent and identically distributed. Furthermore, when the residues are correlated across observations, OLS standard errors can be biased and over or underestimate the true variability of the estimates of the coefficients.

An alternative would be to use the cointegration analysis, namely through the Full Modified Ordinary Least Squares estimators (FMOLS), Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE). However, in our sample can exist not stationary and unobserved common factors affecting one or a few variables in the panel. On the other hand, it is also necessary to consider the possibility of co-integration between the variables between groups (cointegration cross section) as well as within the group of co-integration. Anyway cointegration analysis arises in part in the literature as a response to the complex nature of interactions and dependencies that exist in general over time and through the individual units in the panel.

Therefore, its application in the study was considered as the cross-sectional dimension of our sample comprises was composed by a small number of industries and a small period, and cointegration will be more suited to a larger dimension of the panel.

For all these reasons, we believe that the econometric methodology of the PCSE seems more appropriate given the objectives listed in the introduction and to jointly analyse the three aspects mentioned at the beginning of this section.

With this methodology we intend to analyse the influence on CO_2 emissions (dependent variable) of variables such as the consumption of fossil fuels, energy consumption and production. On the other hand, taking as dependent variable the intensity of CO_2 emissions, we analyse the influence of the ratios previously defined as CI, CE, EI and ES. The study is made for the two groups of Portuguese industries.

The econometric methodology follows Marques and Fuinhas [37]. We employed the following steps: (i) analysis of the presence of heteroskedasticity, panel autocorrelation and contemporaneous correlation, (ii) the PCSE estimator is applied, and (iii) we confirm the robustness of results applying the Random effect estimator (REE), and the Fixed effect estimator (FEE).

For group wise heteroskedasticity, following Baum [38,39], and as reported in Marques and Fuinhas [37], a modified Wald statistic was

[2] We made estimates of beta convergence only for the intensity of emissions and for the two groups of sectors, but these are included in Appendix since not meeting the core objectives of the article.

provided in the residuals of a fixed effect regression model. For analysing the presence of serial correlation, we employed the Wooldridge test for autocorrelation in panel data. The null hypothesis of no first-order autocorrelation is rejected. The existence of cross section independence was tested by applying the parametric test proposed by Pesaran [40] and the semi-parametric test proposed by Frees [41,42], either to Fixed effect estimator or Random effect estimator.

We proposed two models, based on a panel regression analysis of drives of energy related CO_2 emissions, and CO_2 emissions intensity, in Portuguese industrial sectors. The first regression model with two versions (linear and no linear regression) is developed as follows:

Model 1.

$$\begin{aligned}\text{Ln } CO_{2it} = {} & \alpha_{1t} + \beta_{1i} \text{ Ln } \text{FFuel}_{it} + \beta_{2i} \text{ Ln } \text{ECons}_{ct} \\ & + \beta_{3i} \text{ Ln } \text{GDP}_{it} + d_{1i} + d_{1t} + \mu_{it}\end{aligned}$$

where the dependent variable, CO_2 refers to CO_2 emissions, and the explanatory variables are, FFuel that refers to Fossil Fuel consumption, ECons that refers to Energy consumption and GDP that refers to the sector production. We expect all variables to have positive impact on the dependent variable. *i* Refers to the industry sector and *t* to the year. The error term is $\mu_{it} = \rho_{it}\mu_{it-1} + \eta_{it}$, where η_{it} is serially uncorrelated, but correlated over sectors.

In the second regression model we studied the influence on CO_2 emissions intensity (dependent variable) of the factors in which it can be decomposed (explanatory variables). The equation developed as follows:

Model 2.

$$\begin{aligned}\ln\left(\frac{CO_2}{\text{GDP}_{it}}\right) = {} & \alpha_{it} + \beta_{1i} \ln\left(\frac{CO_2}{\text{FFuel}_{it}}\right) \\ & + \beta_{2i} \ln\left(\frac{\text{FFuel}_{it}}{\text{ECons}_{it}}\right) + \beta_{3i} \ln\left(\frac{\text{ECons}_{it}}{\text{GDP}_{it}}\right) \\ & + \beta_{4i} \ln\left(\frac{\text{GDP}_{it}}{\text{GDP}}\right) + d_{2i} + d_{2t} + \mu_{it}\end{aligned}$$

Each factor or driver in this regression can be interpreted as follows: the dependent variable CO_2/GDP_{it}, namely emissions intensity can be influenced by the explanatory variables as the ratio CO_2/FFuel_{it} namely the CO_2 emissions by unit of fossil fuel, the ratio $\text{FFuel}/\text{ECons}_{it}$ namely the fossil fuel-intensity effect, indicates the proportion of total energy consumption from fossil sources, the ratio $\text{ECons}_{it}/\text{GDP}_{it}$, namely energy-intensity effect of economic output, reflecting efficiency of energy use in the industrial sector and the ratio $\text{GDP}_{it}/\text{GDP}$ that reflects the relevance of the sector on the whole industry, that is, the economic structure of industry.

4. Results

4.1. Convergence results

Observing the sigma convergence of CO_2 emissions intensity for the 2 groups of industries (Fig. 1), we can see that there is convergence, which was mostly marked between 1996 and 1999 and between 2003 and 2006. The convergence is more evident for group B.

Analysing sigma convergence for the various factors on which intensity of emissions decomposes (Fig. 2), we can see that in group A, the highest degree of convergence is presented by EI factor, which means, in what concerns energy intensity, those sectors tend to have a similar behaviour. The value for this factor in 2009 is very close to zero (0.062).

ES factor also presents convergence for group A, although not as pronounced. On the other hand, CE and CI factors are irregular in their pattern of convergence. CE tends to converge until 2002, but thereafter diverge and CI offers a wide divergence in 2001 and is back to converge in 2002. This shows that in terms of the mix of fossil fuels used and in terms of the share of fossil fuels in total energy consumption, industrial sectors are not yet harmonised.

As for sigma convergence in group B (Fig. 3), we can see that CI and ES have among themselves a similar trajectory, until 2004. CI has two periods of convergence (2000–02 and 2005—09) and two periods of divergence (1996—99 and 2002—05). ES shows a slight trend of convergence in the period studied. The ratios EI and CE have an irregular route although similar until 2005 and from then CE clearly diverges and EI converges, approaching this indicator to zero. This last ratio is the one with a greater tendency of convergence.

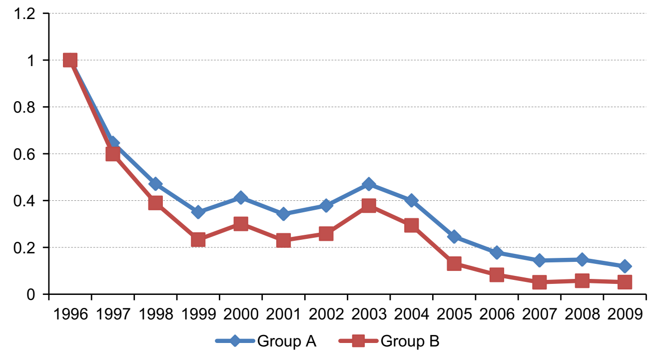

Fig. 1. Sigma convergence of CO_2 emissions intensity.

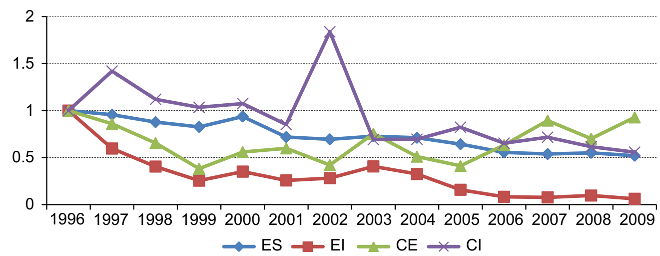

Fig. 2. Sigma convergence for group A.

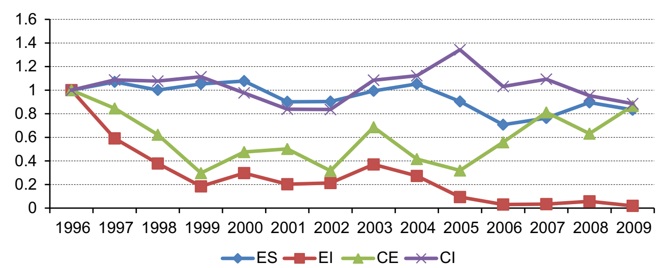

Fig. 3. Sigma convergence for group B.

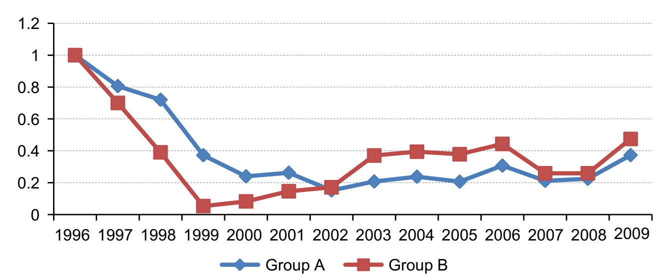

Fig. 4. Gamma convergence of CO_2 emissions intensity.

Regarding gamma convergence, for the intensity of CO_2 emissions (Fig. 4), there was a clear convergence of industries in group A until 2002 and from then there was a slight tendency to diverge. There is a strong convergence in industries group B between 1996–99 and in 2006, and in other years there is a slight divergence. In the overall period the trend in the two groups is for convergence, which is more pronounced in group A.

For group A all ratios have a tendency to converge (Fig. 5). EI appears more unstable with divergence in 2002–03 and 2004–09. CE introduces a period of divergence from 2004. In Fig. 6 it can be seen that for group B the ratios ES and EI have a slight downward trend (convergence) and in some years have values very close to zero (1999 to EI and 2006 to ES). CE and CI present instability with a growing trend (divergence), especially CI. Nevertheless, in some years this indicator is close to zero (1998 and 2000 for CE and 2004 for CI).

Comparing the gamma convergence for the two groups we can see that the trajectory of ES and EI is very similar. The CE ratio between the period 1997 and 2001 is much lower in group B due to a sudden drop of this indicator from 1997 to 1998. After 2001 the trajectory of convergence is very similar for the two groups of industries. The CI ratio in group A has a more stable trajectory of convergence than in group B, in which there are periods of great divergence.

4.2. Econometric results

Initial results of specifications tests are reported in Table 1. The existence of serial correlation was tested and the Wooldridge test for autocorrelation was performed; the results rejected, at the 1% level, the null hypothesis of no first-order autocorrelation for group A and group B. Analysing for possible heteroskedasticity, a modified Wald statistic for group wise heteroskedasticity was used for two industrial group sectors and the result is significant at the 1% level.

The existence of cross section independence was tested applying the Pesaran [40] and Frees [42] procedure either to the fixed effect or the random effect models. We reject the null hypothesis of no cross-sectional dependence, for the 2 groups of industries and for the two models. Globally, the results suggest the evidence of contemporaneous correlation across all the industrial sectors

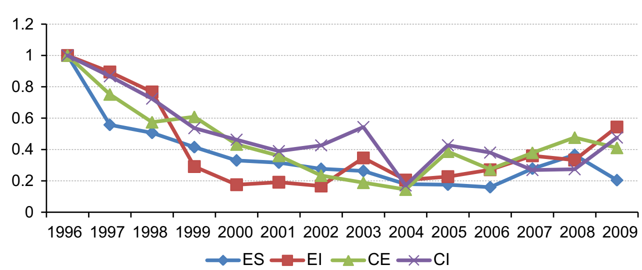

Fig. 5. Gamma convergence for group A.

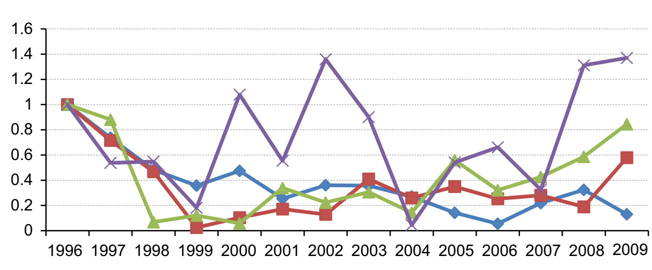

Fig. 6. Gamma convergence for group B.

Table 1
Specification tests.

	Pooled	Random effects	Fixed effects
Model 1-Group A : 16 Industries			
Modified Wald test (χ^2)			57.372***
Pesaran's test		8.940***	4.040***
Frees' test		2.518***	2.624**
Wooldridge test $F(N(0,1))$		409.10***	
Model 2-Group A : 16 Industries			
Modified Wald test (χ^2)			1.3e+08***
Pesaran's test		−1.538	3.254***
Frees' test		2.834***	3.462***
Wooldridge test $F(N(0,1))$	725.58***		
Model 1-Group B : 5 Industries			
Modified Wald test (χ^2)			608***
Pesaran's test		3.556***	1.311
Frees' test		0.239	−0.224
Wooldridge test $F(N(0,1))$	43.28***		
Model 2-Group B : 5 Industries			
Modified Wald test (χ^2)			4.2e+05***
Pesaran's test		0.287	−2.088
Frees' test		0.074	0.538***
Wooldridge test $F(N(0,1))$	49.55***		

Note: The Wooldridge test is normally distributed $N(0,1)$ and tests the null hypothesis of no serial correlation; ***, denote 1% significance level. The Modified Wald Test has χ^2 distribution and tests the null hypothesis. Pesaran test the null hypothesis of cross section independence.

and reveal (through fixed and random effect model), at 1% significance level, the rejection of the null hypothesis of cross sectional independence.

For each Model 1 and 2, we estimated four submodels using PCSE estimator, to evaluate the robustness of the estimations. While presenting the results of the four submodels (in Tables 2 and 3), we only analyse the submodel (III) by considering the most appropriate given the specification test results.

Model 1 reveals for group A and for group B that explanatory variables have, jointly, a great significance explaining CO_2 emissions. From Table 2 we can see that a 1% increase on fossil fuel consumption (natural gas, coal and lignite, petroleum, coke, fuel oil, diesel oil, motor gasoline, LPG and other petroleum products) induces an increase around 92% on CO_2 emissions for all panel group A (16 industries), while a 1% increase in energy consumption induces an increase on CO_2 emissions, around 12%, ceteris paribus. For group B, these impacts are of 58% and 60% respectively.

In the PCSE model 2 we have a good jointly significance of explanatory variables towards CO_2 emissions intensity. The model for group A shows that a 1% increase of the ratio CO_2 emissions by fossil fuel consumption induces an increase of 113% on CO_2 emissions intensity, a 1% increase in the ratio fossil fuel consumption by energy consumption induces an increase of 97% on CO_2 emissions intensity, a 1% increase in the energy intensity ratio induces an increase of 96% on CO_2 emissions intensity and the impact of a 1% change in the economic structure (given by the ratio sectoral GDP/GDP) induces a change of 98% on the dependent variable, ceteris paribus. For group B the magnitude of the impacts is bigger. The values are of 123%, 106%, 103% and 104% for the impacts of explanatory variables mentioned above.

To check the robustness of the results, confirming a possible inefficiency in the estimation of coefficients and bias in the estimation of errors, one should compare the similarity with the estimators obtained through the panel with random effects and fixed effects. If the results are different from the PCSE estimators, the PCSE results are more robust (minimum variance). The results of the estimates for both FEE and REE lead to the erroneous rejection of the power to explain some explanatory variables, such

Table 2
Results of Parsimonious.

Dependent variable $LnCO_{2i,t}$	PCSE			
Independent variables	(I) Corr(AR1)	(II) Corr(psAR1)	(III) Corr(AR1) hetonly	(IV) Corr(linear)
Model 1-Group A				
Ln FFuel	0.91924 (0.000)***	0.96330 (0.000)***	0.91924 (0.000)***	0.97954 (0.000)***
Ln ECons	0.12099 (0.000)***	0.12998 (0.000)***	0.12099 (0.000)***	0.13650 (0.000)***
Ln GDP_i	0.03567 (0.187)	−0.01411 (0.630)	0.03567 (0.182)	−0.10854 (0.000)***
Constant	−10.2873 (0.000)***	−10.709 (0.000)***	−10.287 (0.000)***	−10.429 (0.000)***
Observations	240	240	240	240
R^2/Pseudo R^2	0.9568	0.9806	0.9568	0.9844
Wald (χ^2)	2523 (0.000)***	9619 (0.000)***	2745 (0.000)***	588,757 (0.000)***
Model 1-Group B				
Ln FFuel	0.581885 (0.000)***	0.579763 (0.000)***	0.581885 (0.000)***	0.468375 (0.000)***
Ln ECons	0.600654 (0.000)***	0.481002 (0.000)***	0.600654 (0.000)***	0.82296 (0.000)***
Ln GDP_i	0.012630 (0.436)	0.01366 (0.249)	0.012630 (0.506)	−0.01585 (0.848)
Constant	−12.4141 (0.000)***	−10.235 (0.000)***	−12.4141 (0.000)***	−14.241 (0.000)***
Observations	75	75	75	75
R^2/Pseudo R^2	0.989	0.998	0.989	0.990
Wald (χ^2)	1694 (0.000)***	3386 (0.000)***	1360 (0.000)***	8121 (0.000)***

Note: The Wald test has χ^2 distribution and tests the null hypothesis of non- significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, denote significance at 1% significance level; Corr (AR1) – first-order autoregressive error, Corr (psAR1) – correlation over sectors and autocorrelation sector; Corr (AR1) hetonly – heteroskedastic over sectors and common first order autoregressive error AR(1); Corr (linear) – correlation over sectors and no autocorrelation.

Table 3
Results of Parsimonious.

Dependent variable $CO_2/GDP_{i,t}$	PCSE			
Independent variables	(I) Corr(AR1)	(II) Corr(psAR1)	(III) Corr(AR1) hetonly	(IV) Corr(linear)
Model 2-Group A				
Ln CO_2/FFuel	1.12524 (0.000)***	1.11370 (0.000)***	1.12524 (0.000)***	1.2881 (0.000)***
Ln FFuell/EC	0.970624 (0.000)***	0.984384 (0.000)***	0.970624 (0.000)***	0.98232 (0.000)***
Ln EC/GDP_i	0.958276 (0.000)***	0.962707 (0.000)***	0.958276 (0.000)***	0.95807 (0.000)***
Ln GDP_i/GDP	0.984449 (0.000)***	0.962261 (0.000)***	0.984449 (0.000)***	0.88676 (0.000)***
Constant	1.361855 (0.028)**	1.187062 (0.000)***	1.361855 (0.022)**	2.5969 (0.000)***
Observations	240	240	240	240
R^2/Pseudo R^2	0.9237	0.9801	0.9237	0.9764
Wald (χ^2)	27,370 (0.000)***	33,856 (0.000)***	28,951 (0.000)***	1.01e+06 (0.000)***
Model 2-Group B				
Ln CO_2/FFuel	1.22921 (0.000)***	1.17247 (0.000)***	1.22921 (0.000)***	1.7279 (0.000)***
Ln FFuell/EC	1.05798 (0.000)***	1,04377 (0.000)***	1.05798 (0.000)***	1.07328 (0.000)***
Ln EC/GDP_i	1.03328 (0.000)***	0.997317 (0.000)***	1.03328 (0.000)***	1.00882 (0.000)***
Ln GDP_i/GDP	1.0442 (0.000)***	1.03893 (0.000)***	1.0442 (0.000)***	1.0026 (0.000)***
Constant	1.85526 (0.183)	1.70022 (0.071)*	1.85526 (0.176)	1.46921 (0.082)*
Observations	75	75	75	75
R^2/Pseudo R^2	0.881	0.979	0.881	0.972
Wald (χ^2)	15,372 (0.000)***	33,856 (0.000)***	9361 (0.000)***	154,287 (0.000)***

Note: The Wald test has χ^2 distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; panel corrected standard errors are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; Corr (AR1) – first-order autoregressive error, Corr (psAR1) – correlation over sectors and autocorrelation sector; Corr (AR1) hetonly – heteroskedastic over sectors and common first order autoregressive error AR(1); Corr (linear) – correlation over sectors and no autocorrelation.

as the ratio Fossil Fuel/Energy Consumption and the ratio CO_2/Fossil Fuel. The comparison of both FEE and REE is made regarding the inefficiency in coefficients estimation in three options: Conventional Standard Errors (CSE), Robust Standard Errors (RSE) and First-order Autoregressive Errors (AR (1)).

In fact, those estimators are not well suited to dealing simultaneously with both serial and contemporaneous correlations, for which we found statistical evidence with the PCSE estimator. Therefore, with both results of FEE and REE presented in Table 4, we can see the parameters revealing similar significances into both estimators, and the results of the Wald tests revealing statistical significance at 1% level, rejecting the null hypothesis of non-significance, as a whole of the parameters of the ratio explanatory variables. On the other hand, LM test statistically and strongly reject the null hypothesis of the existence of industrial sectors specific effects. In fact, the results do not invalidate the poor quality and inefficiency for both estimators FEE and REE, while the PCSE estimator is highly efficient; in general the variance of the PCSE estimators is smaller than FEE or REE.

5. Conclusions and policy implications

The need to know if Portuguese industry and energy sectors have the same pattern of emissions, fuel and energy intensity, on the one hand, and which are the long term effects of specific variables on the mitigation of emissions, on the other hand, led us to study the existence of convergence of some relevant ratios. Moreover we studied the influence that the consumption of fossil

Table 4
Results from usual panel data estimators.

Dependent variable Ln $CO_{2i,t}$						
	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects
Independent variables	CSE		RSE		AR(1)	
Model 1-Group A						
Ln FFuel	0.84454 (0.000)***	0.61941 (0.000)***	0.84454 (0.000)***	0.69412 (0.044)**	0.92291 (0.000)***	0.81502 (0.000)***
Ln ECons	0.24544 (0.000)***	0.29538 (0.000)***	0.24544 (0.159)	0.29538 (0.195)	0.12664 (0.001)***	0.12240 (0.002)***
Ln GDP_i	−0.073898 (0.060)*	−0.04977 (0.227)	−0.07389 (0.327)	−0.04977 (0.506)	0.023200 (0.499)	0.06852 (0.085)*
Constant	−10.387 (0.000)***	−7.96367 (0.000)***	−10.387 (0.000)***	−7.9636(0.020)**	−10.3424 (0.000)***	−9.02897 (0.000)***
Observations	240	240	240	240	240	240
F test		88.50 (0.000)***		10.15 (0.000)***		147.81 (0.000)***
Wald (χ^2)	1164.20 (0.000)***		469.40 (0.000)***		1699.09 (0.000)***	
Hausman (χ^2)		14.70 (0.002)***				
Model 1-Group B						
Ln FFuel	0.4637 (0.000)***	0.65898 (0.000)***	0.4637 (0.000)***	0.65898 (0.007)***	0.92291 (0.000)***	0.81502 (0.000)***
Ln ECons	0.82296 (0.000)***	0.16469 (0.055)*	0.82296 (0.000)***	0.16469 (0.280)	0.12664 (0.001)***	0.12240 (0.002)***
Ln GDP_i	−0.00158 (0.937)	0.00045 (0.983)	−0.00158 (0.918)	0.00045 (0.954)	0.023200 (0.499)	0.06852 (0.085)*
Constant	−14.241 (0.000)***	−6.0433 (0.000)***	−14.241 (0.000)***	−6.0433 (0.000)***	−10.3424 (0.000)***	−9.02897 (0.000)***
Observations	75	75	75	75	240	240
F test		65.42 (0.000)***		39.91 (0.002)***		147.81 (0.000)***
Wald (χ^2)	7193 (0.000)***		12,371 (0.000)***	0.65898 (0.007)***	1699.09 (0.000)***	
Hausman (χ^2)		51.83 (0.000)***				
Model 2-Group A						
Dependent variable $CO_2/GDP_{i,t}$						
Ln CO_2/FFuel	1.03767 (0.000)***	1.02676 (0.000)***	1.03767 (0.000)***	1.02676 (0.000)***	1.07412 (0.000)***	0.98498 (0.000)***
Ln FFuel/EC	1.00231 (0.000)***	1.05227 (0.000)***	1.00231 (0.000)***	1.05227 (0.000)***	0.98608 (0.000)***	0.971396 (0.000)***
Ln EC/GDP_i	0.99476 (0.000)***	1.04636 (0.000)***	0.99476 (0.000)***	1.04637 (0.000)***	0.96809 (0.000)***	0.938048 (0.000)***
Ln GDP_i/GDP	0.96688 (0.000)***	1.02978 (0.000)***	0.96688 (0.000)***	1.02978 (0.000)***	0.965222 (0.000)***	1.05280 (0.000)***
Constant	0.19731 (0.809)	−0.13274 (0.878)	0.1973 (0.557)	−0.13274 (0.680)	0.75658 (0.493)	0.42663 (0.405)
Observations	240	240	240	240	240	240
F test		116.51 (0.000)***		798.84 (0.000)***		55.90 (0.000)***
Wald (χ^2)	1025 (0.000)***		18856 (0.000)***		1098 (0.000)***	
Hausman (χ^2)		1.99 (0.737)				
Model 2-Group B						
Ln CO_2/FFuel	1.17279 (0.000)***	1.05519 (0.009)***	1.17279 (0.000)***	1.05519 (0.000)***	1.20824 (0.000)***	0.92992 (0.055)*
Ln FFuel/EC	1.07328 (0.000)***	1.24416 (0.002)***	1.07328 (0.000)***	1.24416 (0.006)***	1.06474 (0.000)***	0.80196 (0.085)*
Ln EC/GDP_i	1.00882 (0.000)***	1.084523 (0.000)***	1.00882 (0.000)***	1.084523 (0.000)***	1.0767 (0.000)***	0.87071 (0.004)***
Ln GDP_i/GDP	1.00262 (0.000)***	1.12903 (0.000)***	1.00262 (0.000)***	1.12903 (0.000)***	1.0346 (0.000)***	0.98885 (0.004)***
Constant	1.46921 (0.563)	0.04450 (0.991)	1.46921 (0.259)	0.04450 (0.951)	1.67607 (0.526)	0.62248 (0.796)
Observations	75	75	75	75	75	75
F test		8.43 (0.000)***		159.45 (0.000)***		3.65 (0.009)***
Wald (χ^2)	2513 (0.000)***		265897 (0.000)***		819 (0.000)***	
Hausman (χ^2)		0.88 (0.927)				

Note: The *F*-test tests the null hypothesis of non-significance as a whole of the estimated parameters; the Wald test has χ^2 distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; $P>|z|$ and $P>|t|$ are reported in brackets. ***, **, *, denote significance at 1%, 5% and 10% significance levels, respectively; CSE – Conventional Standard Errors; RSE – Robust Standard Errors; Corr(AR1) – first-order autoregressive error; the regressions were performed in Stata 12.

fuels, energy and GDP have on CO_2 emissions, and the influence that the ratios in which CO_2 emissions intensity decomposes can affect that variable, using an econometric approach. The analysis was performed for 16 industry and energy sectors (group A) and then for its sub-group of 5 most polluting sectors (group B).

From this analysis we can highlight two set of conclusions. The first one is related with convergence. In what concerns sigma convergence, emissions and energy intensity, sectors tend to have similar behaviour, even these similarities are bigger for industries in group B. There is also convergence in the economic structure, higher for group A. In fact, in 1999 there were more discrepancies between sectoral GDP than in 2009. Sectors with much importance in 1999, as CB, CC and CG decreased its importance significantly (see graph in Appendix A). Particularly in group B, the sectors CG, EC and D lost relative importance in consideration of the CD sector. In terms of the mix of fossil fuels used, industrial sectors are not yet harmonised, that is, there is not a common behaviour between sectors. CI factor is also irregular in its pattern of convergence for the two groups but the trend is to converge, more evident for group A. Therefore, for the intensity of emissions and for energy intensity, there is a trend towards harmonisation of sectors for the whole period, most evident in group B. For emissions by fossil fuel and the structure of the economy there is more harmonisation in group A.

Regarding gamma convergence, in the overall period the trend in the two groups is for convergence for all ratios, which means that the sectors decreased their discrepancies in terms of its rank position, that is, the most polluting sectors decreased their importance in relation to the various ratios studied. An exception is the ratio CI and CE for group B, where sectors did not change their rank position. This reveals difficulties in the change of fossil fuel mix, and in the substitution of fossil fuels by renewable energy, in the most polluting sectors, which does not happen for all industries included in group A.

In the Portuguese industry and energy sectors, the CO_2 emissions intensity and their energy-related drivers were converging towards two distinct industrial groups: one of relatively high CO_2 emissions intensity and the whole group of manufacturing industries. Indeed, when the industry is disaggregated this way, the convergence is more evident in emissions intensity, energy

intensity and the percentage of fossil fuels in the total energy consumption, for group B. It means this group of high emissions intensity has similar energy intensity and energy consumption mix, and that it is well connected in the energy trade and technology transfer systems in the manufacturing industry and other sectors, and that it has common Government commitment for reducing the CO_2 emissions intensity and improving efficiency in the use of energy or shifting toward less fossil fuel consumption.

In the convergence analysis stochastic differences, in the long-term, between industry and energy sectors, means that accumulated random differences in the short-term constitute an explanation to see if the shocks on those series persist over time. This same evidence is of interest to energy policy makers because, evidence of a random shock can reverse the direction wanted to those variables, among others, those that promote productive efficiency in these sectors with the use of new cleaner technologies. This is important to understand, specifically for Portugal, concerning the progressive increase of regulatory incentives in the industrial sectors of energy, particularly in terms of incentives and public policies that promote such investments to producers operating in those industries. On the other hand if there is evidence for differences in the long term of being deterministic, this means that the deterministic random components of the series, over time, are diluted. In this case, policy makers do not need to intervene in certain moment of time, since the same series follows the desired evolution.

The second set of conclusions is related with the econometric approach. For Model 1 we saw that the variables have a significant importance in explaining CO_2 emissions, including the use of fossil fuels and energy consumption. Group B presents a smaller impact in the case of fossil fuels, but larger compared with total energy consumption. For model 2 we have a good jointly significance of explanatory variables towards CO_2 emissions intensity. The ratio CO_2 emissions by fossil fuel consumption, the ratio fossil fuel consumption by energy consumption, the energy intensity and the economic structure, present elasticities of 113%, 97%, 96% and 98% respectively on the dependent variable, ceteris paribus. For group B the magnitude of the impacts is greater. The values are of 123%, 106%, 103% and 104%. This can reinforce the idea that these five sectors included in group B contributed more to the variations on CO_2 emissions intensity in the considered period.

These results show that these ratios are crucial to reducing the CO_2 intensity of Portuguese sectors, especially in the industries listed in Group B, particularly in what concerns increasing energy efficiency and the use of renewable energy, both points focused on European policy (2009/28/CE directive) [43]. European policies are focused on market-based instruments (mainly taxes, subsidies and the CO_2 emissions market), but also in the development of energy technologies (especially technologies dedicated to energy efficiency and renewable energy, or technologies for low-carbon) and the EU financial instruments supporting the achievement of political goals. If the European CO_2 emissions market gives a different treatment for the different sectors, at the level of licences assigned, in other policies there is little or no discrimination between sectors, and what this study shows is that for some variables or particular set of sectors, observed behaviour and the effects obtained are not homogeneous.

Comparing our results with some other studies, we can mention the work of Jobert et al. [30], that based on the results of the analysis of convergence of Portugal and Turkey include them in a specific group called "polluters apprentices", since on the one hand, the growth rate of its CO_2 emissions per capita is very higher than the average, and on the other hand, the convergence paths reveals that CO_2 emissions per capita show small variations in a specific temporal evolution (1995–2005). In a further aspect of the same study, the authors assess the speed of convergence of per capita emissions by the impact of the effect of GDP per capita, population and the share of industry in GDP, revealing their results on the one hand, that per capita GDP is significant only for Germany, Hungary and Ireland; while on the other hand, the share of industry in GDP was considered significant for CO_2 emissions per capita, for Bulgaria, Czech Republic, Germany, Hungary, Ireland, Poland, Portugal, Romania, Sweden and Turkey. These results confirm what we concluded in this study about the importance of convergence effects of industry and energy sectors in CO_2 emissions of Portugal, although our study also differentiate the findings for a group of 5 most polluting sectors.

Miketa and Mulder [44] while considering a period before 1995, make convergence analysis of energy productivity across 56 countries in 10 manufacturing sectors. The authors reveal that there is convergence between countries, particularly for less energy intensive industries, and that this may be caused by differences between countries in terms of productivity in energy sector, not just by the catch-up mechanism, but also by other exogenous and country-specific factors. Mulder and De Groot [27], although making an analysis of decomposition to understand the effects that influence the amount of energy in sectors in the various countries, they analyse only the convergence of several individual sectors in a cross country analysis for the variable energy intensity. Compared to studies Miketa and Mulder [44] and Mulder and De Groot [27], we analysed not only the convergence in energy intensity, but also all the other ratios that explain the intensity of CO_2 emissions. Our approach is different, since the authors referred to disaggregate sectors, but consider the aggregated panel of countries, and we aggregate sectors in a panel and applied to a particular country. Nevertheless we made the distinction in a group where there were the most polluting sectors. Both works show the existence of specific factors to each country, which can influence the intensity of convergence. In this sense it is important to make the study of convergence to a particular country as is the case in our study.

In short, given the studies that evaluated the emissions at the sectoral level, our results are accurate to the level of disaggregated information supporting the hypothesis that, in terms of emissions intensity, its main drivers are connected to different sectoral energy productivity levels. Thus, the breakdown for the subgroup of 5 industrial sectors tend to show the general trend of intensity rates of CO_2 emissions to the overall level of economic activity in Portugal, where convergence tends to be conditioned to specific characteristics of each sector rather unconditional or absolute convergence.

Moreover, in the near future, given the international environmental commitments, our results help to implicitly identify the underlying effects contributing to the growth of emissions intensity, in particular for group B. We assume that in this group could be sectors that individually tend to show faster growth on average than group as a whole.

It seems also reasonable to assume that our results further support the hypothesis that industry and energy sectors with higher emission intensity may suffer from diminishing returns in energy intensities. The sectors with lower emission intensity can benefit from knowledge transfer and technology transfer, whereby the production processes can converge because of increased competition, international exposure and environmental commitments.

It can be pointed three kinds of limitations of this work. The first is related with the fact that the study of convergence applied to the panel sectors, do not give information about the existence of convergence for individual sectors. Although this was not the aim of this study, we present in attachment an application of the KPSS test, by sectors, which does not reveals identical results for stationarity of the series, so the disaggregated level of convergence analysis does not reject the null hypothesis for all individual

sectors. This results show differences in the level of convergence of emission intensities. In a future work, one could also estimate the analysis of convergence for individual sectors, considering the other variables present in this work, which affect the intensity of emissions.

A second limitation is related with the time horizon used, which can be considered short, although other studies reported in the literature, have used timeframes also reduced (see Mulder and De Groot [27]).

Another limitation is due to the lack of data available regarding the consumption of renewable energy with the disaggregation for industry which was necessary for this study. Although in an implicit way, we find that the inclusion of the ratio (fossil fuel/total energy) also provides us with useful information concerning the use of renewable energy, because, if one sector decreases this ratio, it is because more non-fossil energy, or rather, renewable energy, is being used. However, we hope to have enough data in the near future in order to make estimates with sufficient disaggregation, using concrete values for renewable energy.

In a future research is relevant to identify that the share of fossil and renewable energy sources are important in explaining differences in emissions intensity among industry and energy sectors. For that purpose, a parametric stochastic frontier approach using some maximum entropy estimators, namely the generalised maximum entropy and the generalised cross-entropy, could be applied for explain the energy-related CO_2 emissions. This maximum entropy approach can assess technical and environmental efficiency, for which contribute factors such as capital, labour, but also consumption of fossil and renewable energies.

Appendix A

Estimation of beta convergence (stochastic and deterministic) for CO_2 emissions intensity

This complementary empirical strategy on this section follows in particular the work by Strazicich and List [23] and the work by Romero-Ávila [45]. We employed the case of convergence in CO_2 emissions intensity at the sectoral level. For that purpose, we compute the logarithm of the CO_2 emissions intensity levels for the sample of 16 industry and energy sectors in Portugal. The normalisation of sectoral-specific emissions against average emissions, allows us to distinguish sectoral-specific movements from common trends in emissions caused by global shocks, such as the dependence of the group of the 5 most polluting sectors (concerning emissions intensity), composed mainly by energy sectors.

Stochastic convergence

The Panel on Table A2 reports the results of the univariate KPSS tests. Column 2 focuses on the specification with time trends, which corresponds to the notion of stochastic convergence. Among the 16 industry and energy sectors, we are able to reject the null hypothesis of stationarity at 1% level for four sectors – manufacture of basic pharmaceutical products and pharmaceutical preparations, manufacture of rubber and plastic products, and other non-metallic mineral products, manufacture of basic metals and fabricated metal products, except machinery and equipment, manufacture of furniture, other manufacturing: repair and installation of machinery and equipment; – at the 5% level we are able to reject the null for eleven sectors – mining and quarrying, manufacture of textiles, wearing apparel and leather products, manufacture of wood and paper products, manufacture of coke, and refined petroleum products, manufacture of chemicals products, manufacture of computer, electronic and optical products, manufacture of electrical equipment, manufacture of machinery and equipment, manufacture of transport equipment, electricity, gas, steam and air-conditioning supply, water, sewerage, waste management and remediation activities; – and at the 10% level for only one sector – manufacture of food products, beverages and tobacco products. In sum, the univariate KPSS tests point to divergence in relative CO_2 emissions intensity in all manufacturing sectors.

Deterministic convergence

This notion of convergence allows emissions in one sector to move in parallel over the long run relative to average emissions intensity. According to the Panel in Table A2 , second column, univariate KPSS tests fail to reject the stationarity null hypothesis at conventional significance levels for the specification without trends for seven specific sectors: manufacture of textiles, wearing apparel and leather products, manufacture of basic metals and fabricated metal products, except machinery and equipment, manufacture of computer, electronic and optical products, manufacture of machinery and equipment, manufacture of transport equipment, electricity, gas, steam and air-conditioning supply, water, sewerage, waste management and remediation activities; – at 10% level we are able to reject the null hypothesis for nine others sectors.

Table A3 reports the results from the panel stationarity test of Hadri for the case of cross-sectional independence, for the case of homogeneity and heterogeneity in the estimation of the long-run variance. Remarkably, we are able to reject the null of joint stationarity at 1% significance level for the case of cross-independence.

With the panel KPSS test assuming cross-independence we strongly reject the null hypothesis of regime-wise trend stationarity in relative CO_2 emissions intensity at the 1% level, thus supporting divergence in CO_2 emissions intensity for all 16 industry and energy sectors. This is likely to derive from the higher statistical power of the panel statistic through exploiting the cross-sectional variation of the data.

Thus, industry and energy sectors with structural differences will tend to grow toward their own pollution level, and convergence becomes conditional upon sector characteristics. In this

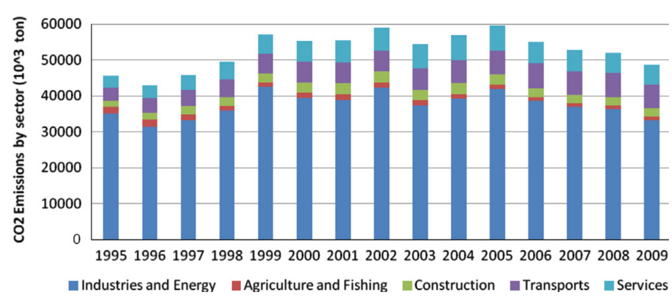

Fig. A1. Evolution of CO_2 emissions in Portugal by sectors in 1995–2009.
Source: Own elaboration using data from INE. Statistics Portugal. National Accounts.

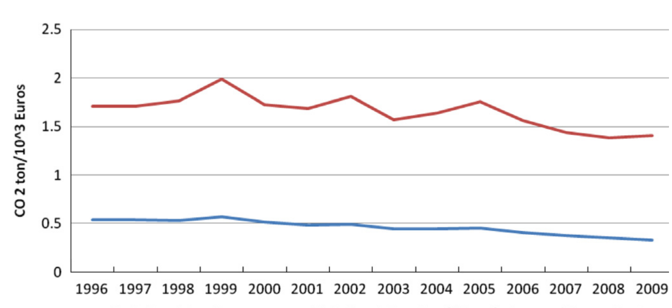

Fig. A2. Evolution of Portuguese emissions intensity 1996–2009.
Source: Own elaboration using data from INE. Statistics Portugal. National Accounts.

case, conditional b-convergence is naturally investigated by adding a set of exogenous explanatory factors (in our case, the drivers of energy-related CO_2 emissions) to the absolute b-convergence regression.

See Figs. A1–A4 and Tables A1–A3.

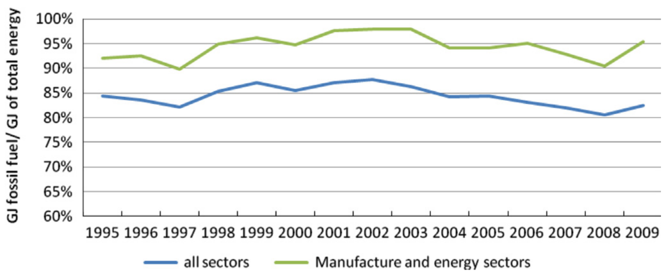

Fig. A4. Weight of fossil fuels in total energy consumption 1995–2009.
Source: Own elaboration using data from INE. Statistics Portugal. National Accounts.

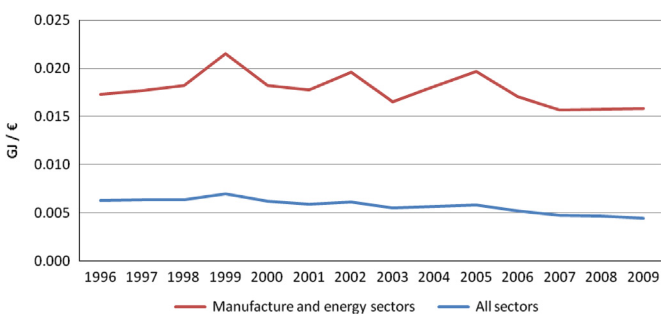

Fig. A3. Evolution of Portuguese energy intensity 1996–2009.
Source: Own elaboration using data from INE. Statistics Portugal. National Accounts.

Table A1
National accounts classification by industry.

A10	A38	Description
Group A		
2	B	Mining and quarrying
2	CA	Manufacture of food products, beverages and tobacco products
2	CB	Manufacture of textiles, wearing apparel and leather products
2	CC	Manufacture of wood and paper products, and printing
2	CD	Manufacture of coke, and refined petroleum products
2	CE	Manufacture of chemicals and chemical products
2	CF	Manufacture of basic pharmaceutical products and pharmaceutical preparations
2	CG	Manufacture of rubber and plastics products, and other non-metallic mineral products
2	CH	Manufacture of basic metals and fabricated metal products, except machinery and equipment
2	CI	Manufacture of computer, electronic and optical products
2	CJ	Manufacture of electrical equipment
2	CK	Manufacture of machinery and equipment n.e.c.
2	CL	Manufacture of transport equipment
2	CM	Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment
2	D	Electricity, gas, steam and air-conditioning supply
2	E	Water, sewerage, waste management and remediation activities
Group B		
2	B	Mining and quarrying
2	CD	Manufacture of coke, and refined petroleum products
2	CE	Manufacture of chemicals and chemical products
2	CG	Manufacture of rubber and plastics products, and other non-metallic mineral products
2	D	Electricity, gas, steam and air-conditioning supply

Table A2
Estimators of beta convergence.

KPSS stationarity test		
Panel: Sectoral-specific tests	Stochastic convergence trend	Deterministic convergence no trend
Mining and quarrying	0.194**	0.425*
Manufacture of food products, beverages and tobacco products	0.212*	0.392*
Manufacture of textiles, wearing apparel and leather products	0.186**	0.328
Manufacture of wood and paper products, and printing	0.212**	0.348*
Manufacture of coke, and refined petroleum products	0.208**	0.391*
Manufacture of chemicals and chemical products	0.215**	0.377*
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.268***	0.387*
Manufacture of rubber and plastics products, and other non-metallic mineral products	0.281***	0.401*
Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.271***	0.338
Manufacture of computer, electronic and optical products	0.212**	0.301
Manufacture of electrical equipment	0.209**	0.369*
Manufacture of machinery and equipment	0.216**	0.327
Manufacture of transport equipment	0.205**	0.324
Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment	0.270***	0.383*
Electricity, gas, steam and air-conditioning supply	0.184**	0.274
Water, sewerage, waste management and remediation activities	0.184**	0.333

Note: The 1%, 5% and 10% finite-sample critical values for the KPSS test for the specification are compared with the values computed for each time-series, which result of max lags (7) are chosen by Schwert criterion. **, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively.

Table A3
Panel KPSS test.

	Tests	*p*-Value
Specification with trends		
LM homogeneous (5 sectors)	6.433***	0.000
LM heterogeneous (16 sectors)	11.548***	0.000
Specification without trends		
LM homogeneous (5 sectors)	2.194**	0.014
LM heterogeneous (16 sectors)	4.0112**	0.000

Note: LM_homogeneous and LM_heterogeneous denote the panel KPSS test of Hadri for the case of homogeneity and heterogeneity in the estimation of the long-run variance, respectively. *** and ** imply rejection of the null hypothesis at 1% and 5%, respectively.

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